Journal of Empirical Finance 57 (2020) 16–32

Contents lists available at ScienceDirect

Journal of Empirical Finance

journal homepage: www.elsevier.com/locate/jempfin

Testing moving average trading strategies on ETFs[☆]

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A R T I C L E I N F O

JEL classification:
G11
G14
D83

Keywords:
Moving average
Technical trading rules
Data-snooping bias
Exchange traded funds

A B S T R A C T

The evidence for the profitability of MA strategies documented in the literature is usually based on non-tradable indices or portfolios/factors and the use of the zero return or risk-free rate as the benchmark. In this paper we implement MA strategies using ETFs and examine the performance of such strategies using a variety of risk-adjusted performance measures. We find that relative to the buy-and-hold strategy, MA strategies have lower average returns and Sharpe ratios, but fare better under factor-adjusted performance measures such as the CAPM alpha. We also find that MA strategies become less profitable when they are implemented using ETFs than using their underlying indices. In addition, we propose a quasi-intraday version of the standard MA strategy (QUIMA) that allows investors to trade immediately upon observing MA crossover signals. The QUIMA strategy outperforms the standard one that only trades at the close of a trading day, when the long-term MA lag length is no more than 50 days.

1. Introduction

Moving average (MA) is one of the most basic and well-known technical trading rules.[1] In its simplest form, the so called variable holding length moving average (VMA) strategy requires buying whenever the short-term MA crosses above the long-term MA (i.e., *golden cross*), and selling when the short-term MA dives below the long-term MA (i.e., *death cross*). Given the simplicity of the MA trading rule, it is not surprising that researchers doubt that any documented MA profitability can persist in an increasingly efficient market. However, since the seminal work of Brock et al. (1992), there has been growing evidence that the MA strategy does generate statistically significant profit (e.g. Han et al., 2013 and Neely et al., 2014). The question then arises: if the MA profitability is persistent and robust, can and/or should retail investors utilize such profitability?

First of all, most studies of the MA strategy, especially those finding evidence of profitability, use zero returns or the risk-free rate as the performance benchmark, while in reality investment strategies are often benchmarked to the buy-and-hold market return. The buy-and-hold benchmark is especially relevant for retail investors, given that passive investing is often considered to be a suitable strategy for such investors. Secondly, the MA strategy is usually back-tested on non-tradable indices or factor portfolios in the literature. In practice, however, it may not be feasible for retail investors to implement an MA strategy using such indices or portfolios. On the other hand, equity ETFs are viable instruments for retail investors.

In this study we shed light on these two issues. We conduct our investigation in three steps. First, we examine the performance of MA strategies against a buy-and-hold (BH) strategy using equity ETFs in the US market. We find that MA strategies do not always

☆ We thank Kewei Hou (editor), an associate editor, an anonymous referee, Andrew Ainsworth, Yufeng Han, Paul Hsu, Fuwei Jiang, and seminar participants at University of Wisconsin-Milwaukee, Rochester Institute of Technology, the 2014 China International Conference in Finance, the 2015 Midwest Finance Association meeting, and the 2015 Financial Management Association meeting for their helpful comments and suggestions. We also thank Shasta Shakya for her excellent research assistance.

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1 For studies of other technical trading signals see, e.g., Brown et al. (1998), Lo et al. (2000), and Hsu et al. (2016).

https://doi.org/10.1016/j.jempfin.2019.10.002
Received 19 March 2018; Received in revised form 27 September 2019; Accepted 2 October 2019
Available online 8 October 2019
0927-5398/

outperform the passive BH benchmark. Relative to the BH benchmark, MA strategies have lower average return and Sharpe ratios, but perform better under factor-adjusted performance measures such as the CAPM alpha and the appraisal ratio.

Next, we explore why MA strategies may underperform the BH strategy. To this end, we compare MA strategies implemented using a (non-tradable) index with the same MA strategies implemented using an ETF based on the same index. Our results show that there is a performance reduction if MA strategies are tested on ETFs. That is, the performance of MA strategies drops when they are applied to liquid and tradable ETFs.

Lastly, we explore another possible reason why standard MA strategies may underperform the BH strategy by proposing a modified version of the standard MA strategy considered in the literature. Under the standard MA strategy using daily data, an investor only trades at the close of a trading day, even though an MA crossover can happen at any time. On the other hand, it is quite natural for investors to respond immediately when a trading signal occurs. As such, we consider a *quasi-intraday MA strategy* (QUIMA) that trades immediately upon seeing an MA crossover signal. We find that the QUIMA strategy outperforms the standard MA strategy when the long-term MA lag length is no more than 50 days.

To summarize, this paper examines the performance of MA strategies using ETFs against a variety of benchmarks. We find that MA strategies underperform the buy-and-hold strategy in terms of the average return or the Sharpe ratio. On the other hand, MA strategies outperform the buy-and-hold strategy under the CAPM alpha.

The remainder of the paper proceeds with a brief literature review in Section 2. Section 3 describes our data. Section 4 introduces the MA strategies implemented in this paper in detail. Section 5 reports the results from our empirical analysis. Section 6 concludes.

2. Literature review

Most tests on the MA strategy are benchmarked on zero return or the risk-free rate in the literature. For instance, Brock et al. (1992) find that daily returns are 7 bps (basis points) higher on days when a short-term MA is above the long-term MA, compared to days when the order is reversed. Bessembinder and Chan (1998) report a 0.22% one-way break-even transaction cost before the positive MA return goes away when tested on the Dow Jones Industrial Average (DJIA) index. LeBaron (1999) reports that the Sharpe ratio of MA tested on foreign exchange prices is robust to the transaction cost of 0.1%. Sullivan et al. (1999) demonstrate that the profitability is not caused by data-snooping.

Several other studies do compare the MA strategy against the buy-and-hold strategy albeit using non-tradable portfolios. For instance, Allen and Karjalainen (1999) and Ready (2002) find that the MA strategy fails to outperform a buy-and-hold benchmark on the S&P500 index or the DJIA index. On the other hand, Han et al. (2013) and Shynkevich (2012) show that the MA strategy can outperform the buy-and-hold strategy on less liquid securities: while the former study uses volatility and size deciles, the latter considers the technology industry and small cap sector portfolios.

Another related study is that of Hsu et al. (2010), who examine the predictive ability of MA strategies without data snooping bias; however, they focus on the performance of such strategies before and after a particular ETF is introduced—and they do not use the buy-and-hold benchmark. Several other recent applications of the moving average rule are also worth noting. Neely et al. (2014) show that technical indicators, including six MA predictors, can predict the US equity premium in- and out-of-sample. Avramov et al. (2018) find that cross-sectionally, stocks with their 21-day MA far away from the 200-day MA continue to move away from the 200-day MA. Huang et al. (2019) provide evidence that using high-dimensional technical indicators (that include MA ones) can help predict bitcoin returns.

Nonetheless, it is still an open question whether or not MA strategies can outperform the buy-and-hold strategy on liquid securities such as ETFs. Additionally, we examine the performance of the QUIMA strategy, a new MA strategy proposed in this study.

3. Data

We consider three major equity indices: the S&P 500 index (S&P500), the Dow Jones Industrial Average (DJIA), and the NASDAQ-100 index, and their corresponding ETFs whose tickers are: SPY, DIA, and QQQ (previously QQQQ), respectively. We retrieve daily data on these indices and ETFs from the Center for Research in Security Prices (CRSP). We download all daily data of ETFs (SHRCD=73) dated before December 31, 2016, which include a total of 2186 ETFs. We also get daily value-weighted market returns (data item "VWRETD") and daily risk-free returns (data item "TDYLD") from the CRSP database. The daily value-weighted market return is the total return on a value-weighted market portfolio excluding American depository receipts.

Daily prices from CRSP include open, high, low, and close prices. Using the adjustment factors that we back out from the dividend-adjusted daily returns, we adjust the four prices to reflect dividend payments. We also manually adjust prices of 16 ETFs that have splits, and fix 8 obvious data entry errors in prices. With the four daily prices for a given ETF, we are able to determine if there is at least one intraday MA crossover in a particular day, and possibly trade immediately around the long-term moving average where an MA crossover occurs.

Since we test MA strategies under various long-term moving average lag lengths ranging from 5 days to 200 days, we require a fairly long price history on ETFs to reduce the impact of booms and busts in the stock market. Therefore, our first filter requires ETFs to have more than 10 years of available data. To avoid survivorship bias, we keep those ETFs launched before December 31, 2006 (10 years before the end of our sample period), no matter how long they have existed. This leaves us with 386 ETFs out of a total of 2186. Our second filter is to remove any ETFs tracking international markets or sectors, because the overnight movement in foreign markets causes big opening gaps, making the MA strategy impossible to trade at the long-term MA price. After removing 64 international ETFs, we have 322 ETFs left. The third filter we apply in ETF selection is focusing on the large and liquid ETFs

Table 1
Summary statistics of ETFs in the sample.

ETF type	N	Annual return (%)	Sharpe ratio	CAPM Alpha (%)	Size (million $)	Turnover (# of Times)
Index/Market	15	10.93	0.40	1.15	9,186	32.48
Style	100	8.86	0.37	0.40	1,467	3.88
Sector	83	6.55	0.25	−0.01	725	14.74
All ETFs	198	8.05	0.32	0.29	1,741	10.60

This table presents the summary statistics of ETFs for the full sample as well as for the three subsamples by ETF type. For each of the three ETF types, we report its average *Annual Return*, *Sharpe Ratio*, one-factor *CAPM Alpha*, ETF *Size*, and annual *Turnover* ratio. All values are annualized from daily data by multiplying 252, except for the Sharpe ratio by which we multiply $\sqrt{252}$. In calculating the one-factor alpha, we use the CRSP value-weighted market return as the benchmark. For all these measures, we first calculate the time-series average for each ETF through its lifetime, then take the average across ETFs within that sample group.

from four major series: the SPDR series, the BlackRock iShare series, the Vanguard series, and the Invesco PowerShares series. Applying this filter reduces the sample to 220 ETFs. Finally, since our performance benchmark is the buy-and-hold return, we focus on long-only ETFs in the equity market. Thus, we exclude six ETFs on fixed-income, three on real estate, five on commodities, and eight short/ultrashort products. The final sample includes 198 long-only equity ETFs.

Table 1 shows summary statistics of these 198 ETFs divided into three groups: index or market ETFs, style ETFs, and sector ETFs. Among the three groups, index or market ETFs are the largest in terms of size (assets under management). Surprisingly, these broad market ETFs have a large positive average CAPM alpha benchmarked on the value-weighted market return. We find the high average alpha is driven by a few ETFs tracking small stocks, such as the Russel 2000 (IWM) and S&P 1000 (SMD). Overall these ETFs have good liquidity as indicated by the high turnover ratio. Investors trade ETFs heavily, with ETF shares on average changing hands more than 10 times each year.

4. Moving-average trading strategies

In this section, we first review the MA strategy which trades only at daily close (the standard MA strategy). We then introduce the QUIMA strategy that responds to MA signals immediately intraday. Finally, we present a simple time-varying transaction cost model to estimate the intraday transaction cost.

4.1. The standard MA strategy

Following Brock et al. (1992), we focus on the simplest form of the MA strategy: the variable length MA (VMA). In this strategy, a position opened in response to an MA crossover will be held until an opposite MA signal is observed, so the total holding time is not fixed. Brock et al. (1992) also defined the fixed-length MA rule in which a position is always closed after a fixed number of days, ignoring any trading signals in between. We select VMA because it is less subject to data-snooping bias as the strategy has one fewer exogenous variable (number of holding days) to select.[2] In addition, VMA has the nice feature that the strategy responds to every trading signal because buy and sell signals always occur alternately.

We implement a long-only strategy here since our benchmark is the passive buy-and-hold strategy on the same security. In other words, we focus on the relative, rather than the absolute, performance of the MA strategy.[3] While the MA trading rule is aimed to capture big price trends, sometimes there could be too many signals when the short- and long-term MAs are entangled. To reduce the number of trades, a band (as a percentage of the long-term MA) around the long-term MA can be introduced so that an MA crossover only gets confirmed when the short-term MA crosses the long-term MA far enough. For our main results, we focus on the case with no band, but we also test the case with a 0.5% band for robustness.

We define the standard MA at day d for past L days as follows:

$$MA_{d,L} = \frac{1}{L}(P_d + P_{d-1} + \cdots + P_{d-L+2} + P_{d-L+1}) \tag{1}$$

where P_d stands for the closing price of day d. As described in, e.g., Hsu et al. (2010), an MA crossover signal may occur at the close of a trading day, and the strategy return starting from the next trading day is updated to the "buy" ("sell") return if it is a golden (death) cross signal. In this paper, the buy status is 100% long position in the tested security, and the sell status is the all cash position earning the risk-free return.

[2] There are other versions of the MA strategy used in practice such as the EMA (exponentially weighted moving average). Those strategies bring in more exogenous variables to weigh historical prices differently.

[3] For robustness, we also tested a long–short strategy as used in Bajgrowicz and Scaillet (2012). The performance of the long–short strategy is worse than the long-only strategy because even on those short days the average return is still positive. This is not surprising given the roughly 10% average market annual return, and similar results have been reported in many studies about market anomalies when a long–short strategy is used. For example, Jegadeesh and Titman (1993) in their Table 1 find all past loser portfolios (the short leg) still have positive returns.

4.2. The quasi-intraday moving average trading strategy

While a golden or death cross can happen anytime during a trading day, the standard MA waits until the close of a trading day to respond to a signal generated during that trading day. This possible delay causes a potential loss of performance for the MA strategy. For instance, for the 198 ETFs included in our sample, when the short- and long-term moving averages have lag lengths of 1 and 10 days, respectively, and there is no band or transaction cost, the average daily return is 1.58% when there is a golden cross, and −1.54% for days with death crosses. If we can realize partial profit or avoid some loss on these MA signal days by responding to signals more promptly, the performance of the MA trading strategy is likely to improve.

We implement a quasi-intraday moving average (QUIMA) trading strategy that trades immediately when an MA crossover occurs, then unwind the trade at close if the cross is later reverted before the close. This setting reflects the common practice to trade on a signal as soon as possible, and then cut losses if the signal turns out to be unconfirmed. As the concept of "intraday" is introduced here, it is necessary to clearly define the calculation of moving averages and the detection of MA crossovers at *any time within a trading day*. We describe the details of the QUIMA strategy below focusing on the calculation of intraday moving averages, detecting confirmed and reverted intraday MA crossovers, trading strategies under different situations, the effect of opening gaps, and an overall evaluation of the new strategy using statistics on days with MA crossover signals.

4.2.1. Quasi-intraday MA crossovers

Intraday MA is similar to standard MA as defined in Eq. (1) except that we replace the closing price P_d in Eq. (1) with an intraday price P_d^t at time t of that day. Therefore, intraday MA at time t of day d is:

$$MA_{d,L}^t = \frac{1}{L}(P_d^t + P_{d-1} + \cdots + P_{d-L+2} + P_{d-L+1}) \tag{2}$$

As we can see, intraday MA is equivalent to a standard MA assuming that the current price is going to be the closing price.

Let us denote by m and n the short- and long-term MA lags, respectively, and by B the band around the long-term MA in percentage. On day d, a quasi-intraday golden cross is detected at the *earliest* time t when:

$$(1)\ MA_{d-1,m} \le MA_{d-1,n}(1+B\%) \qquad \text{and} \qquad (2)\ MA_{d,m}^t > MA_{d-1,n}(1+B\%) \tag{3}$$

A quasi-intraday death cross is detected when:

$$(1)\ MA_{d-1,m} \ge MA_{d-1,n}(1-B\%) \qquad \text{and} \qquad (2)\ MA_{d,m}^t < MA_{d-1,n}(1-B\%) \tag{4}$$

In both the golden and the death cross cases, the first condition determines the order of the short- and long-term MA at the close of the previous trading day, while the second condition checks if that order is *ever* switched during the trading day, even if it just happens temporarily.[4] One assumption here is that an investor calculates the short-term MA using real-time intraday price information, but presets the long-term MA at the beginning of each trading day based on historical daily closing prices. This setting matches with the real world situation when investors constantly evaluate the current price based on a predetermined trading plan, as illustrated by the old saying: "Plan your trade and trade your plan". An alternative setting is to use the real-time intraday long-term MA ($MA_{d,n}^t$) instead of the lagged long-term MA ($MA_{d-1,n}$) in condition (2). This algorithm, under the special condition that t is at the daily close, is actually used in the existing literature. As explained in Ready (2002), a trader must estimate slightly before the close of each trading day whether or not there will be an MA crossover for that day. However, these two algorithms should be very similar since replacing one historical price with the current price has very little impact when the MA lag is long.

For simplicity, let the short-term moving average be the average for one day, i.e., the stock price itself, and assume that $B = 0$. Suppose that a quasi-intraday golden (death) cross occurs on day d, which means that on day $d-1$ the stock price must have closed below(above) the long-term MA. Referring to condition (2) in Eqs. (3) and (4), a quasi-intraday golden cross is detected if $P_d^H > MA_{d-1,n}$ while a quasi-intraday death cross occurs when $P_d^L < MA_{d-1,n}$. Here $P_d^H(P_d^L)$ is the daily high(low) price on day d. So basically, we check the daily high and low prices against the lagged long-term MA to detect quasi-intraday crossovers.

In the general case when short-term MA lag length $m > 1$ and $B > 0$, the quasi-intraday MA crossover condition is

$$\frac{1}{m}(P_d^H - P_{d-m}) > MA_{d-1,n}(1+B\%) - MA_{d-1,m} \tag{5}$$

for golden crosses and

$$\frac{1}{m}(P_{d-m} - P_d^L) > MA_{d-1,m} - MA_{d-1,n}(1-B\%) \tag{6}$$

for death crosses. The left hand sides of these inequalities are the maximum impact on the short-term MA caused by daily high or low prices, and the right hand side represents the distance required for an MA crossover to occur at the beginning of a trading day.

[4] There are two more technical details in identifying quasi-intraday MA crossovers. One is the initial condition that the long-only investor started with 100% cash, so only a golden cross which is a buy signal will be responded to. The other complexity is that when there is a band B, the strategy relies on the type of previous MA signal (golden or death) to determine the order of the short- and long-term MAs, as condition (1) could be satisfied in both Eqs. (3) and (4) at the same time when B is non-zero.

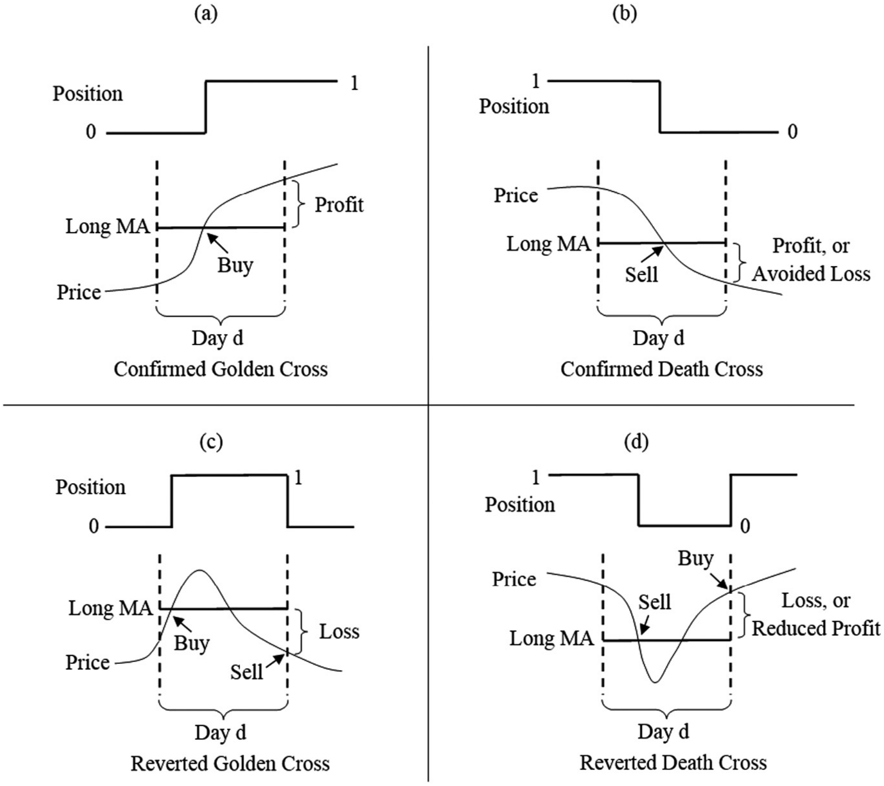

Fig. 1. Figures (a) through (d) illustrate the quasi-intraday moving average trading strategy in four basic cases, respectively: confirmed golden cross, confirmed death cross, reverted golden cross, and reverted death cross. In each case, we identify the buy/sell trading signals and the corresponding change in portfolio position, with 1 indicating a full position invested in the stock and 0 for a full position in the risk-free asset. Also, to the right side of each figure we mark the intraday profit/loss relative to the standard MA strategy.

4.2.2. *The QUIMA trading strategy*

When a quasi-intraday golden cross is detected, the QUIMA strategy buys immediately at the long-term MA price. If the closing price on day d (P_d) also holds above the lagged long-term MA ($MA_{d-1,n}$), this is a confirmed golden cross so that the long position is carried over to the next trading day. This scenario is very similar to the standard MA strategy in the existing literature which buys at the close of day d, except that the investor now also enjoys part of the positive return on signal day d. However, if the closing price on day d eventually reverts back below the lagged long-term MA, the investor would have to unwind the intraday trade around the day d closing price, suffering a loss plus round-trip transaction costs. The situation of death cross is similar, in which the QUIMA strategy avoids partial loss on the MA signal day if the death cross is confirmed, or foregoes some profits plus paying transaction costs in the reverted case. Overall, there are a total of four cases in this QUIMA strategy after an MA crossover signal is detected: confirmed golden cross, confirmed death cross, reverted golden cross, and reverted death cross. Fig. 1 illustrates the MA signals, the timing of trades, the change in portfolio positions, and the daily profit/loss under these four situations.

4.2.3. *Loss from opening gaps*

When implementing the QUIMA strategy, there is a special situation when the opening price on day d gaps up (down) directly above (below) the lagged long-term MA. If that happens, in all of the four cases in Fig. 1 the strategy has to buy(sell) immediately using a market order at the unfavorable opening price instead of the long-term moving average. An alternative treatment is putting a limit order to buy at or below (or sell at or above) the lagged long-term MA. Then, there is a chance the limit order is never filled, which can be detected if the daily low(high) price is higher(lower) than the lagged long-term MA for golden(death) crosses. If that happens, the QUIMA strategy has to trade at the close of day d, likely at an even worse price relative to the opening price. Fig. 2 compares the two different strategies dealing with MA crossovers at opening gaps: market order v.s. limit order, for both the golden cross and the death cross cases. In each scenario, there are three possible price paths: confirmed and missing MA, confirmed but reaching MA, and reverted (which always crosses MA). Obviously, only the first case – confirmed and missing MA – is in favor of the market order strategy. However, our statistics show that the two strategies on how to treat opening gaps perform roughly the same, since the open-to-close price movement is generally larger than the MA-to-open difference, and the confirmed and missing MA case happens slightly more often. In other words, the price path in favor of the market order occurs more frequently and with better returns than the other two paths which benefit the limit order.

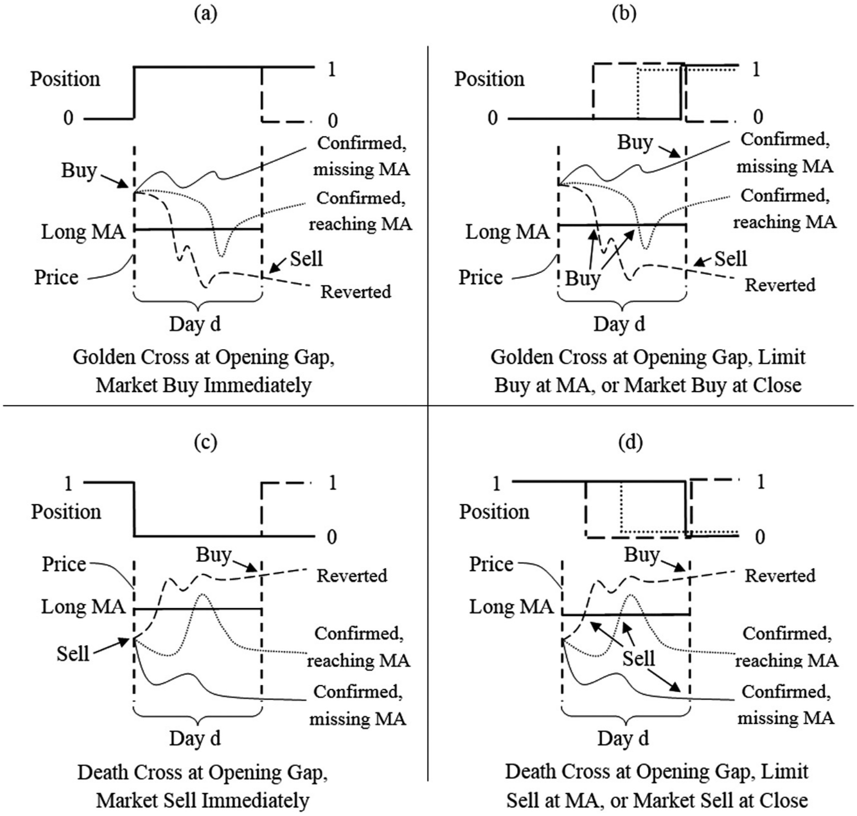

Fig. 2. Figures (a) through (d) illustrate the quasi-intraday moving average trading strategy when a trading signal is generated by an opening gap. Whenever there is a cross at opening, there are three possible scenarios: the solid line is the case when the price confirms the cross at close and never reverts back to the long-term MA; the dotted line is the case when the price confirms the cross at close but temporarily reverts back to the long-term MA within the trading day; and finally the dashed line is the case when the price reverts back to the long-term MA and stays on the other side at closing. Figures (a) and (b) are for golden crosses while figures (c) and (d) are for death crosses. In figures (a) and (c), the strategy buys(sells) immediately at opening, which is a less favorable price than the long-term moving average. In cases (b) and (d), the strategy puts a limit order to buy(sell) at the more favorable price of the long-term moving average, but risks the possibility that the limit order will never be filled if the price does not revert to the long-term MA in that day (the solid line scenario). If that is the case, the strategy has to buy(sell) at the closing price.

Table 2
Summary statistics of MA signals at opening gap.

Case Description	(1) N of Samples	(2) Signal Day Ret	(3) Gap	(4) Open-Close Ret	(5) MA-Open Ret	(6) Score
Golden/Confirmed/Miss	13,993	1.67%	1.13%	0.58%	0.74%	81.03
Golden/Confirmed/Reach	8,410	1.17%	0.90%	0.26%	0.45%	−37.77
Golden/Reverted	10,280	−0.41%	0.93%	−1.35%	0.43%	−43.79
Death/Confirmed/Miss	12,025	−1.74%	−1.15%	−0.64%	−0.75%	76.59
Death/Confirmed/Reach	6,715	−1.17%	−0.79%	−0.38%	−0.36%	−24.15
Death/Reverted	10,175	0.42%	−0.79%	1.21%	−0.38%	−38.18
Total score						13.74

This table summarizes the frequencies (*N of Samples*) of the three possible paths when there is an MA crossover signal at opening gap, the average signal day return (*Signal Day Ret*), size of the opening gap (*Gap*), intraday returns from open to close (*Open-Close Ret*) and returns from the lagged long-term MA to opening price (*MA-Open Ret*). We also calculate a performance score (*Score*) for each case by multiplying the number of samples by the size of open-to-close return for the confirmed/missing MA cases, or multiplying the number of samples by the negative of the size of MA-to-open return for the other four cases. The total score (*Total Score*) is the sum of scores over six cases, with positive(negative) values indicating the advantage of the market(limit) order strategy over the other. The short and long-term moving averages used in this table are 1 and 10 days, respectively, and there is no band or transaction cost.

Table 2 summarizes the frequencies of the three possible paths when there is a quasi-intraday MA crossover at opening gap (column 1), the average signal day return (column 2), the average opening gap return (column 3), the average intraday returns from open to close (column 4), and the returns from the lagged long-term MA to opening price (column 5). In column 6, we calculate a performance score for each case by multiplying the total number of samples by the corresponding return that captures

Table 3
Summary of eight cases on MA signal days.

Panel A: Statistics of eight cases					
Case Description	(1) N of Samples	(2) Signal Day Ret	(3) MA Ret	(4) Gap Loss	(5) Performance Gain/Loss
Golden, Confirmed, No Gap	30,013	1.65%	0.67%	0.00%	0.67%
Golden, Confirmed, With Gap	22,403	1.48%	0.55%	0.54%	0.55%
Golden, Reverted, No Gap	18,278	0.24%	−0.71%	0.00%	−0.71%
Golden, Reverted, With Gap	10,280	−0.41%	−1.28%	0.38%	−1.28%
Death, Confirmed, No Gap	33,773	−1.54%	−0.87%	0.00%	0.67%
Death, Confirmed, With Gap	18,740	−1.54%	−0.93%	0.52%	0.61%
Death, Reverted, No Gap	26,912	−0.18%	−0.77%	0.00%	−0.59%
Death, Reverted, With Gap	10,175	0.42%	−0.74%	0.33%	−1.17%
Weighted Avg	N/A	0.01%	−0.40%	0.1705%	0.0741%

Panel B: Confirmed v.s. Reverted					
Case Description	N of Samples	Signal Day Ret	MA Ret	Gap Loss	Performance Gain/Loss
Golden, Confirmed	52,416	1.58%	0.62%	0.23%	0.62%
Golden, Reverted	28,558	0.00%	−0.91%	0.14%	−0.91%
Death, Confirmed	52,513	−1.54%	−0.89%	0.19%	0.65%
Death, Reverted	37,087	−0.01%	−0.77%	0.09%	−0.75%

This table presents the summary statistics on days with an MA crossover signal for the 198 ETFs in our sample. The short and long-term MA lag lengths are 1 and 10 days, respectively, and there is no band or transaction cost. In Panel A, signal days are grouped into eight cases determined by the direction of the crossover (Golden/Death), the type of the crossover (Confirmed/Reverted), and whether or not the signal occurs at the opening gap. For each case, we report the number of samples, followed by averages of the total signal day return (Signal Day Ret), the return captured by the QUIMA strategy (MA Ret), the performance loss caused by opening gaps (Gap Loss), and the overall performance gain or loss on the MA signal day compared to the standard MA strategy. Performance gain/loss is just the MA strategy return (MA Ret) if the signal is a golden cross, or the MA strategy return (MA Ret) minus the signal day return (Signal Day Ret) if it is a death cross. The last line is the average of these statistics weighted by the number of samples. Panel B repeats the panel A statistics focusing on four cases only.

the performance gain under that case. Specifically, the absolute value of open-to-close return (column 4) is the gain for the two confirmed-and-missing-MA cases, and the size of MA-to-open return (column 5) is the gain for the other four cases. As a result, the choice of using limit or market order is just weighing the trade-off between performance gains from the confirmed-and-missing-MA case and that from the other four cases. We use the total score in the last row in Table 2 to summarize this tradeoff, with positive(negative) values indicating the advantage of the market(limit) order strategy.

The long-term MA lag length in Table 2 is set to be 10 days (in an untabulated analysis, we run 21 different MA lengths ranging from 5 days to 200 days and find similar results). We find that the market order strategy at opening gap is better when long-term MA lag length is shorter than 50 days, while the limit order strategy prevails in cases with longer MA lag lengths. Overall, the two strategies on opening gaps do not generate too much difference, and we use the market order strategy for the remaining analysis in this study. In a related paper, Berkman et al. (2012) find that buying at opening when there is a gap up is not optimal since prices are likely to reverse during the trading day. Our finding implies that the small portion of overnight movements that are not reverted later are more likely to trigger MA crossovers. Therefore, while many overnight movements end up getting reverted, the few big ones mostly continue their trend during the day, especially when the long-term MA lag is shorter than 50 days.

4.2.4. Tradeoff on days with MA signals

The QUIMA strategy reaps extra profits by trading quickly after an MA signal is observed, but suffers from reverted intraday crossovers as well as losses from opening gaps. Table 3 presents detailed summary statistics on days with MA signals for the 198 ETFs in our sample. Panel A calculates the average signal day returns (column 2), QUIMA strategy returns (column 3), and losses from opening gap (column 4) for eight cases partitioned by golden or death crosses, confirmed or reverted crosses, and those occurring at the opening gap or not. Column 5 is the performance gain/loss relative to the standard MA strategy if trading at the close of the signal day. Panel B condenses the information in Panel A into only four cases focusing on the comparison between confirmed and reverted MA crossovers. In Panel B, we notice that if an MA signal is eventually confirmed, the QUIMA strategy captures about 40% of the entire signal day return, or 0.63%. If an MA signal is later reverted, the QUIMA strategy incurs a daily loss of about 0.83%, plus round-trip transaction costs. With reverted crosses happening 63% as often as confirmed crosses, the overall improvement on MA signal days is $0.63\% - 0.83\% * 0.63 = 0.11\%$ excluding transaction costs. This overall improvement already accounts for the loss from opening gaps listed in column 4. Therefore, according to these statistics, the proposed QUIMA strategy should be able to outperform the standard MA strategy when the one-way transaction cost for ETFs is no more than 5 bps.

4.3. Transaction costs

Transaction cost is important for this study because we are comparing trading strategies with different trading frequencies. The buy-and-hold benchmark strategy does not trade over time. The standard MA strategy trades once on days with an MA crossover

Table 4
Performance comparison: MA versus buy-and-hold strategies.

Panel A: MA strategies v.s. the buy-and-hold benchmark

Strategy	Return (%)			Sharpe ratio			Alpha (%)			Appraisal ratio		
	MA	BH	Diff	MA	BH	Diff	MA	BH	Diff	MA	BH	Diff
QUIMA	5.80	8.05	−2.25***	0.3433	0.3232	0.0200	2.59	0.29	2.30***	0.2143	0.0724	0.1418***
Standard	4.51	8.05	−3.54***	0.2641	0.3232	−0.0591***	1.26	0.29	0.98***	0.1120	0.0724	0.0396**
QUIMA w. TC	4.38	8.05	−3.67***	0.2473	0.3232	−0.0760***	1.17	0.29	0.88**	0.1065	0.0724	0.0341*
Standard w. TC	3.83	8.05	−4.22***	0.2184	0.3232	−0.1048***	0.59	0.29	0.30	0.0602	0.0724	−0.0122

Panel B: Alpha and appraisal ratio

	CAPM alpha (%)					Appraisal ratio				
	No TC		With TC			No TC		With TC		
Long MA	QUIMA-BH	Standard-BH	QUIMA-BH	Standard-BH	BH	QUIMA-BH	Standard-BH	QUIMA-BH	Standard-BH	BH
5	8.61***	−4.01***	3.64***	−6.57***	0.29	0.5949***	−0.3567***	0.2272***	−0.5462***	0.0724
10	2.14***	−3.43***	−1.31***	−5.17***	0.29	0.1154***	−0.3066***	−0.1368***	−0.4360***	0.0724
20	3.05***	−0.78**	0.73*	−1.97***	0.29	0.1963***	−0.1121***	0.0215	−0.1980***	0.0724
30	2.77***	0.24	0.83**	−0.66**	0.29	0.1822***	−0.0311*	0.0388*	−0.0997***	0.0724
40	2.21***	0.01	0.58	−0.73**	0.29	0.1339***	−0.0475**	0.0088	−0.1068***	0.0724
50	2.31***	0.81***	0.84**	0.16	0.29	0.1461***	0.0250*	0.0313	−0.0268*	0.0724
60	2.00***	1.12***	0.61*	0.56**	0.29	0.1258***	0.0503***	0.0202	0.0051	0.0724
70	1.75***	1.10***	0.54	0.57**	0.29	0.1088***	0.0521***	0.0138	0.0085	0.0724
80	1.91***	1.66***	0.79**	1.17***	0.29	0.1212***	0.1026***	0.0321	0.0627***	0.0724
90	2.24***	1.99***	1.20***	1.53***	0.29	0.1416***	0.1250***	0.0583***	0.0872***	0.0724
100	2.17***	1.98***	1.13***	1.52***	0.29	0.1342***	0.1234***	0.0540**	0.0872***	0.0724
110	2.01***	1.88***	1.02***	1.42***	0.29	0.1211***	0.1139***	0.0433**	0.0783***	0.0724
120	1.99***	1.93***	1.00***	1.50***	0.29	0.1227***	0.1173***	0.0487**	0.0837***	0.0724
130	1.83***	1.86***	0.88**	1.43***	0.29	0.1082***	0.1095***	0.0380*	0.0756***	0.0724
140	1.81***	1.93***	0.93***	1.47***	0.29	0.1079***	0.1173***	0.0411*	0.0838***	0.0724
150	1.71***	1.97***	0.88**	1.53***	0.29	0.0980***	0.1220***	0.0350*	0.0900***	0.0724
160	1.66***	1.96***	0.86**	1.55***	0.29	0.0928***	0.1212***	0.0318	0.0913***	0.0724
170	1.48***	1.94***	0.71**	1.60***	0.29	0.0767***	0.1179***	0.0176	0.0910***	0.0724
180	1.50***	1.95***	0.77**	1.62***	0.29	0.0783***	0.1150***	0.0220	0.0885***	0.0724
190	1.60***	2.13***	0.91***	1.82***	0.29	0.0872***	0.1324***	0.0342*	0.1074***	0.0724
200	1.60***	2.24***	0.96***	1.94***	0.29	0.0852***	0.1398***	0.0355*	0.1167***	0.0724

This table compares MA strategies and the buy-and-hold benchmark strategy on four performance measures: *Return*, *Sharpe Ratio*, one-factor *Alpha*, and *Appraisal Ratio*, annualized by multiplying daily returns and alphas by 252, and multiplying daily Sharpe ratios and appraisal ratios by $\sqrt{252}$. In Panel A, we report four cases for the QUIMA strategy and the standard MA strategy, each with or without transaction costs as detailed in Section 4.3. Each of the MA performance value is the average performance of 21 strategies with the long-term MA lag ranging from 5 days to 200 days, then average across the 198 ETFs in our sample. Each BH performance value is the average across the 198 ETFs. For all MA strategies, the short-term MA lag is 1 day (the ETF price) and there is no band. Difference (*Diff*) is the performance of the MA strategy minus that of the BH strategy. In Panel B, we further compare the CAPM alphas and the appraisal ratios between MA and BH strategies under different long-term MA lengths. We report the average differences in alpha and appraisal ratio for both the QUIMA strategy and the standard MA strategy, with an without transaction costs. Significance of the performance difference is based on bootstrapping 10,000 times. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.

signal, while the QUIMA strategy incurs extra transactions on other days when an intraday MA signal is not confirmed at close. Instead of using a fixed level of transaction cost for all ETFs at any time, we estimate the intraday transaction cost using the CRSP daily bid–ask spread data following a recent study by Chung and Zhang (2014) which finds that intraday bid–ask spread is highly correlated with the CRSP bid–ask spread at the daily close. In their Table 2, Chung and Zhang (2014) show that (1) the intraday spread is smaller than the CRSP spread; (2) cross-sectionally, this reduction is higher for large (more liquid) stocks when the CRSP spread is low; and (3) over time, CRSP spread drops a lot after the decimalization in 2001. Therefore, a straightforward method is to first find out the average CRSP spread in our ETF sample before and after the decimalization, then match with size quintiles in Chung and Zhang (2014) for a corresponding reduction level to get the intraday spread.

Specifically, in our entire sample the average CRSP bid–ask spread is 25.15 bps. Before decimalization, it is 175.23 bps, while that number drops to only 20.75 bps after decimalization. According to Chung and Zhang (2014), Table 2, Panel C, the third size quintile for all NYSE/AMEX stocks has an average CRSP spread of 153 bps, comparable to our pre-decimalization sample. For this quintile, intraday spread is on average CRSP spread divided by 2.5. Similarly, the largest size (i.e., most liquid) quintile matches with our post-decimalization data, and we should divide the CRSP spread by a ratio of 3.5 to get the intraday spread. Finally, the one-way intraday transaction cost is just half of the estimated intraday bid–ask spread:

$$TC_{i,t} = 0.5 \times CRSP\_Spread_{i,t}/2.5 \qquad \text{before April 9, 2001, and} \tag{7}$$

$$TC_{i,t} = 0.5 \times CRSP\_Spread_{i,t}/3.5 \qquad \text{on or after April 9, 2001} \tag{8}$$

where $TC_{i,t}$ and $CRSP\_Spread_{i,t}$ are the estimated one-way transaction cost and the daily CRSP spread for ETF i on trading day t, respectively. After applying this model to our ETF samples, we find the average one-way intraday transaction cost is 3.95 bps which is in line with the 5 bps fixed transaction cost used in Hsu et al. (2010). Across ETFs, VUG (Vanguard Growth) has the lowest average transaction cost at 1.1 bps. SPY's average is 2.7 bps. Following a few delisted ETFs, SLYV (SPDR Small Cap Value ETF) has the highest transaction cost averaging 15.4 bps among currently existing ETFs.

5. Empirical results

In this section, we first check whether or not MA strategies can beat the passive buy-and-hold benchmark, then validate the QUIMA strategy by comparing its performance with that of the standard MA strategy, with or without transaction costs. Section 5.3 compares MA performances between indices and their corresponding ETFs. In Section 5.4 we further look at what factors affect the profitability of the MA strategy. Liquidity is clearly one consideration, which can more or less explain why existing literature found mixed results about the profitability of the MA strategy. We also find that MA profitability is sensitive to trader exploitation so that ETFs have larger opening gaps than corresponding indices, making them less profitable for the QUIMA strategy. Finally, we document that among various MA lag lengths, the 10-day lag seems to be widely used by investors as its performance is notably worse than nearby MA lag lengths. Unless noted otherwise, the short-term MA lag is one day (the stock price), and there is no transaction cost or band around the long-term MA.

5.1. Performances of the MA and BH strategies

Table 4 compares the performance between MA strategies and the buy-and-hold benchmark. In Panel A, we focus on the aggregate performance by averaging 21 different strategies with long-term MA lag lengths ranging from 5 days to 200 days. Each row lists one of the four cases of the MA strategy including the newly proposed QUIMA strategy and the standard MA strategy used in the existing literature, both with and without transaction costs. Across columns we report four performance measures: strategy return, Sharpe ratio, CAPM alpha, and the appraisal ratio which is the alpha divided by the residue standard deviation from the CAPM regression. The last performance measure, appraisal ratio, tells us whether or not the CAPM alpha is magnified by taking high risks (see, e.g., Agarwal and Naik, 2000). The strategy return and CAPM alpha are annualized by multiplying daily values by 252, while daily Sharpe ratio and appraisal ratio need to be multiplied by $\sqrt{252}$.[5]

When calculating performance differences, one concern is that ETFs cover mostly the same sample period, so there is high performance correlation across ETFs. Another concern is that our sample size is not very large. Therefore, instead of a standard t-test, we use the bootstrap method in Hull et al. (2004) to calculate statistical significance. Specifically, we first demean the performance differences to get a sample with zero mean. We then resample with replacement for 10,000 times on the demeaned sample, calculating t-statistics for each of the bootstrapped sample. This way, we get a null distribution of t-statistics. Finally, significance is calculated by comparing the t-statistic of the true sample to the simulated null distribution.

We find the MA strategies cannot beat the buy-and-hold benchmark in terms of average return and Sharpe ratio. In Table 4, Panel A, MA strategies greatly underperform the buy-and-hold benchmark in strategy return, and their Sharpe ratios are also significantly lower in three out of the four cases. On the other hand, MA strategies have higher CAPM alpha as well as the appraisal ratio. Panel B of Table 4 further compares the alphas and appraisal ratios between MA and BH strategies across different long-term MA lags. We can see the higher risk-adjusted performance of the MA strategy is quite consistent across different parameter settings, except for the 10-day long-term MA, which we will discuss more in Section 5.4.3.

Our results show that when evaluated under the one-factor alpha, MA strategies beat the market by about 2% without transaction cost, while the buy-and-hold strategy only has an average alpha of 0.29%. This outperformance in alpha is not due to higher risk as the appraisal ratio measure also leads to the same conclusion. By looking into individual ETFs, we find the superior alpha of MA strategies is mainly driven by delisted or under-performing ETFs. As a trend-chasing strategy, MA strategies help investors to control risk when the underlying asset is doomed. In our sample, the worst buy-and-hold alpha is −19.75% from the iShares Dow Jones U.S. Internet ETF (IYV) which was launched at the peak of the dot-com bubble in May 2000, and got delisted in December, 2002. Dropping from \$56.42 per share to \$9.17, IYV brings huge losses to buy-and-hold investors. In contrast, MA strategies are able to get out of the downward spiral while still profiting from rebounds, growing 85% during IYV's lifetime under the setting of 10-day long-term MA length, QUIMA, and no transaction cost. We also run a robustness check to remove the 15 delisted ETFs from our sample. The results hold with slightly improved MA performances while the average buy-and-hold alpha is still only 0.60%.

Overall, we find MA strategies underperform the buy-and-hold benchmark in average return and Sharpe ratio, but have a superior CAPM alpha because they allow traders to get out of big bearish movements of under-performing ETFs.

5.2. Performances of the QUIMA and the standard MA strategies

Table 5 further compares the QUIMA strategy to the standard MA strategy at each long-term MA lag length ranging from 5 days to 200 days. Panel A presents the results without transaction cost, while Panel B repeats the same analysis after applying the time-varying intraday transaction cost estimated from the CRSP daily bid–ask spread.

As we can see from Table 5, Panel A, without transaction cost, the QUIMA strategy is superior to the standard MA strategy in most cases, especially when the long-term MA lag is no more than 70 days. When there is a transaction cost in Panel B, the QUIMA strategy performs better when the long-term MA lag length is shorter than 50 days, while the standard MA strategy dominates in

[5] We also test using natural logarithm to calculate daily returns as in Ready (2002). The results are almost identical since daily returns are so small that compounding causes very little impact in these calculations.

Table 5
Performance comparison: QUIMA v.s. Standard MA.

Panel A: Performance comparison with no transaction cost

Long MA	Return (%)			Sharpe ratio			Alpha (%)			Appraisal ratio		
(Days)	QUIMA	Standard MA	Diff	QUIMA	Standard MA	Diff	QUIMA	Standard MA	Diff	QUIMA	Standard MA	Diff
5	12.61	0.00	12.61***	0.7343	−0.0500	0.7843***	8.90	−3.72	12.62***	0.6674	−0.2843	0.9517***
10	5.95	0.49	5.46***	0.3298	−0.0145	0.3443***	2.43	−3.14	5.57***	0.1878	−0.2341	0.4219***
20	6.69	2.93	3.75***	0.3954	0.1406	0.2548***	3.34	−0.49	3.83***	0.2688	−0.0397	0.3084***
30	6.27	3.78	2.50***	0.3804	0.2027	0.1777***	3.06	0.52	2.53***	0.2547	0.0413	0.2133***
40	5.70	3.53	2.17***	0.3378	0.1874	0.1503***	2.50	0.30	2.20***	0.2063	0.0250	0.1814***
50	5.80	4.35	1.46***	0.3487	0.2509	0.0978***	2.60	1.10	1.50***	0.2185	0.0975	0.1210***
60	5.49	4.65	0.84***	0.3308	0.2730	0.0577***	2.29	1.40	0.89***	0.1982	0.1227	0.0755***
70	5.23	4.63	0.60**	0.3143	0.2727	0.0416***	2.04	1.39	0.64**	0.1813	0.1245	0.0568***
80	5.38	5.16	0.21	0.3250	0.3159	0.0091	2.20	1.95	0.25	0.1936	0.1751	0.0185*
90	5.69	5.47	0.21	0.3436	0.3354	0.0082	2.53	2.28	0.25	0.2141	0.1975	0.0166
100	5.60	5.45	0.16	0.3367	0.3329	0.0038	2.46	2.27	0.18	0.2067	0.1959	0.0108
110	5.44	5.33	0.11	0.3251	0.3250	0.0000	2.30	2.17	0.14	0.1935	0.1863	0.0072
120	5.42	5.39	0.03	0.3266	0.3287	−0.0020	2.28	2.22	0.05	0.1951	0.1897	0.0054
130	5.25	5.31	−0.06	0.3131	0.3217	−0.0086	2.12	2.15	−0.03	0.1806	0.1820	−0.0014
140	5.23	5.37	−0.14	0.3124	0.3277	−0.0153	2.10	2.22	−0.12	0.1803	0.1898	−0.0094
150	5.13	5.41	−0.28*	0.3028	0.3314	−0.0286***	2.00	2.25	−0.25*	0.1704	0.1945	−0.0240**
160	5.08	5.40	−0.32**	0.2982	0.3295	−0.0313***	1.95	2.25	−0.30**	0.1652	0.1936	−0.0284***
170	4.90	5.38	−0.48***	0.2838	0.3261	−0.0423***	1.77	2.23	−0.46***	0.1491	0.1903	−0.0412***
180	4.92	5.39	−0.47***	0.2849	0.3233	−0.0383***	1.79	2.24	−0.46***	0.1507	0.1874	−0.0367***
190	5.02	5.57	−0.56***	0.2934	0.3396	−0.0462***	1.89	2.42	−0.54***	0.1596	0.2049	−0.0453***
200	5.02	5.67	−0.65***	0.2909	0.3457	−0.0547***	1.89	2.53	−0.63***	0.1576	0.2122	−0.0546***

Panel B: Performance comparison with transaction cost

Long MA	Return (%)			Sharpe ratio			Alpha (%)			Appraisal ratio		
(Days)	QUIMA	Standard MA	Diff	QUIMA	Standard MA	Diff	QUIMA	Standard MA	Diff	QUIMA	Standard MA	Diff
5	7.64	−2.56	10.21***	0.4247	−0.2104	0.6350***	3.93	−6.28	10.21***	0.2996	−0.4738	0.7733***
10	2.50	−1.25	3.75***	0.1098	−0.1244	0.2342***	−1.02	−4.89	3.86***	−0.0643	−0.3636	0.2993***
20	4.37	1.75	2.62***	0.2412	0.0655	0.1757***	1.02	−1.68	2.70***	0.0939	−0.1255	0.2195***
30	4.33	2.88	1.45***	0.2517	0.1417	0.1100***	1.11	−0.37	1.49***	0.1113	−0.0273	0.1386***
40	4.08	2.79	1.28***	0.2258	0.1351	0.0906***	0.87	−0.44	1.31***	0.0812	−0.0344	0.1156***
50	4.33	3.70	0.63***	0.2458	0.2052	0.0406***	1.13	0.45	0.68***	0.1038	0.0457	0.0581***
60	4.10	4.10	0.00	0.2354	0.2333	0.0021	0.90	0.85	0.05	0.0926	0.0775	0.0151
70	4.01	4.09	−0.08	0.2287	0.2342	−0.0055	0.82	0.86	−0.04	0.0863	0.0810	0.0053
80	4.26	4.68	−0.42**	0.2447	0.2806	−0.0358***	1.08	1.46	−0.38**	0.1045	0.1351	−0.0306**
90	4.65	5.02	−0.37**	0.2684	0.3018	−0.0334***	1.49	1.82	−0.33**	0.1307	0.1597	−0.0290**
100	4.57	4.98	−0.41***	0.2636	0.2999	−0.0363***	1.42	1.81	−0.38**	0.1264	0.1597	−0.0332***
110	4.45	4.87	−0.43***	0.2541	0.2925	−0.0385***	1.30	1.71	−0.40***	0.1158	0.1507	−0.0350***
120	4.43	4.96	−0.53***	0.2589	0.2980	−0.0391***	1.28	1.79	−0.51***	0.1211	0.1561	−0.0350***
130	4.30	4.88	−0.58***	0.2487	0.2906	−0.0419***	1.17	1.72	−0.55***	0.1104	0.1480	−0.0376***
140	4.35	4.91	−0.57***	0.2512	0.2973	−0.0460***	1.22	1.76	−0.54***	0.1135	0.1562	−0.0427***
150	4.30	4.97	−0.68***	0.2450	0.3022	−0.0572***	1.17	1.82	−0.66***	0.1074	0.1624	−0.0550***
160	4.28	4.99	−0.71***	0.2423	0.3024	−0.0600***	1.15	1.84	−0.69***	0.1043	0.1638	−0.0595***
170	4.14	5.03	−0.90***	0.2295	0.3014	−0.0719***	1.00	1.88	−0.88***	0.0900	0.1635	−0.0735***
180	4.19	5.06	−0.86***	0.2333	0.2988	−0.0656***	1.06	1.91	−0.85***	0.0945	0.1610	−0.0665***
190	4.33	5.26	−0.93***	0.2446	0.3164	−0.0718***	1.20	2.11	−0.91***	0.1066	0.1798	−0.0732***
200	4.37	5.38	−1.00***	0.2450	0.3243	−0.0792***	1.25	2.23	−0.99***	0.1079	0.1891	−0.0813***

This table compares the QUIMA strategy with the Standard MA strategy across different long-term MA lag lengths. In Panel A there is no transaction cost while in Panel B we apply the time-varying transaction cost as detailed in Section 4.3. The short-term moving average is 1 day (the ETF price) and there is no band. We present four performance measures: *Return*, *Sharpe Ratio*, one-factor *Alpha*, and *Appraisal ratio*, annualized by multiplying daily returns and alphas by 252, and multiplying daily Sharpe ratios and appraisal ratios by $\sqrt{252}$. Difference (*Diff*) is the performance of the QUIMA strategy minus that of the standard MA strategy. For all these measures, we first calculate the time-series average for each ETF, then average across 198 ETFs. Significance is based on bootstrapping 10,000 times. The last two rows in Panel B also list the four performance measures of the buy-and-hold strategy on ETF itself and the value-weighted market return. The ETF buy-and-hold performance is annualized, averaged over time for each ETF, then averaged across ETFs. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively.

longer lag lengths. The performance of the QUIMA strategy erodes more because there is an additional round-trip transaction cost when there is a reverted MA crossover. The finding that the QUIMA strategy works better with short long-term MA lag is quite intuitive. Based on statistics shown in Table 3, the QUIMA strategy does slightly better than the standard MA strategy on MA signal days. Therefore, more frequent MA crossovers under shorter long-term MA lag lengths help the QUIMA strategy. In addition, we find in untabulated results that when the long-term MA lag length is short, the intraday MA crossovers are more “decisive” in the sense that there are more confirmed rather than reverted MA crossovers. This makes sense as in the investment community, longer MAs represent stronger price support or resistance. Intraday attempts to cross longer MA is therefore less likely to hold throughout the day.

Table 6
ETF and index performance comparison using the QUIMA strategy.

Long MA	(1) SPY	(2) S&P500	(3) Diff	(4) DIA	(5) DJIA	(6) Diff	(7) QQQ	(8) NASDAQ-100	(9) Diff
(Days)	From 02/01/1993			From 01/20/1998			From 03/11/1999		
5	6.35	21.04	−14.68***	7.78	15.43	−7.66***	4.48	4.90	−0.42
10	4.42	14.93	−10.52***	6.82	11.81	−4.99***	3.68	3.61	0.07
20	5.88	13.69	−7.81***	6.78	10.29	−3.51***	8.87	7.38	1.49
30	5.78	10.87	−5.10***	5.54	9.26	−3.73***	6.21	6.88	−0.67
40	5.19	11.48	−6.29***	5.06	8.24	−3.18***	8.98	7.59	1.39
50	6.41	10.31	−3.90***	4.34	8.13	−3.79***	7.51	7.30	0.21
60	5.70	10.00	−4.30***	3.51	7.41	−3.90***	6.39	8.02	−1.64
70	6.07	10.54	−4.47***	3.30	7.24	−3.94***	7.72	7.44	0.27
80	6.36	10.25	−3.89***	2.12	5.65	−3.53***	7.98	8.46	−0.49
90	5.57	9.62	−4.06***	3.06	6.94	−3.88***	7.04	7.91	−0.87
100	6.14	9.94	−3.81***	2.12	5.95	−3.82***	6.55	8.33	−1.78
110	6.92	9.80	−2.88***	1.81	6.04	−4.23***	4.02	4.93	−0.92
120	6.96	10.67	−3.71***	3.11	6.23	−3.11***	5.58	6.74	−1.16
130	6.72	10.18	−3.46***	2.40	6.09	−3.69***	4.86	6.81	−1.95
140	6.81	9.91	−3.10***	2.99	7.12	−4.14***	6.11	6.34	−0.23
150	7.21	9.75	−2.54***	3.52	7.62	−4.10***	6.67	7.13	−0.45
160	6.52	9.21	−2.69***	3.98	6.86	−2.88***	5.91	7.22	−1.31
170	6.56	9.34	−2.77***	2.69	6.25	−3.56***	5.42	6.06	−0.63
180	6.62	9.48	−2.86***	3.26	6.38	−3.12***	5.68	6.65	−0.97
190	6.96	9.92	−2.96***	3.31	6.78	−3.47***	5.16	6.64	−1.48
200	7.48	9.85	−2.37***	3.55	6.17	−2.62***	4.13	6.34	−2.20*
Rt Corr	97.75%			98.13%			92.41%		
OC Rt Corr	84.59%			80.20%			83.58%		
Buy and Hold	10.35	10.30	0.04	8.82	8.75	0.07	9.40	9.41	−0.01
Market	10.35	10.35		8.39	8.39		7.50	7.50	

In this table we test the QUIMA strategy on three major market indices S&P500, Dow Jones Industrial Average (DJIA), and Nasdaq-100, in comparison with their corresponding tracking ETFs: SPY, DIA, and QQQ (formerly QQQQ). The short-term moving average is 1 day (the ETF price) and the long-term MA lag lengths ranges from 5 to 200 days as listed in the first column. There is no band or transaction cost. All results are annualized strategy returns. The difference (*Diff*) of each pair is calculated by subtracting the index performance from the ETF performance. Statistical significance is calculated using a standard t-test on daily returns. At the bottom of this table, we also report the return correlations (*Rt Corr*) and the open-to-close return correlation (*OC Rt Corr*) of each ETF-index pair, the annualized buy-and-hold return of each security (*Buy-and-Hold*), as well as the value-weighted market return over the same period (*Market*). Numbers reported in columns 2 through 10 are in percentage. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

In unreported tables, we also run a robustness test for the case with 0.5% band around the long-term MA. Under this setting, the trading signal will not be triggered immediately when an MA crossover occurs. Instead, we wait until the distance between the short-term and long-term MAs enlarges to 0.5% of the long-term MA level to confirm a trading signal. The results remain the same for the standard MA strategy. For the QUIMA strategy, adding a band around long-term MA slightly reduces the performance, because there are fewer trading signal days that benefit the QUIMA strategy as shown in Table 3.

5.3. Performance comparison between ETFs and indices

Table 6 compares the performance in terms of annualized returns of the QUIMA strategy on indices versus on ETFs. We see that the QUIMA strategy performs much better on the non-tradable S&P500 and DJIA indices than on tradable ETFs of SPY and DIA. Among different MA lengths, the performance difference is larger when the long-term MA lag length is not too long. However, there is not much difference between the NASDAQ-100 index and its tracking ETF, QQQ. Toward the end of Table 6, we also report two types of return correlations between ETFs and indices. The first line *Rt Corr* is using the total holding period return which is the close-to-close return plus dividend if any. The second line *OC Rt Corr* uses the open-to-close return that excludes overnight return and dividend. We can see while ETFs track closely to their corresponding indices in terms of total holding period return, the open-to-close returns are not in perfect alignment between ETFs and indices. We could infer that the open prices of ETFs may not track indices as closely as close prices do. The last two rows in Table 6 list the buy-and-hold strategy performance as well as the market return. As we can see, only some QUIMA strategies on the S&P and DJIA indices outperform buy-and-hold returns of the same security.

Table 7 repeats the comparison using the standard MA strategy which is used in the existing literature. In this case, we still observe slight, but not significant, under-performance of strategies on ETFs relative to indices. Because the standard MA strategy on both ETFs and indices underperform the buy-and-hold benchmark, we do not find the standard MA having higher return than BH in a long-only portfolio as documented in the literature. A close look at the literature reveals that papers testing the MA trading rule on indices mostly use zero or the risk-free rate as the performance benchmark such as in Brock et al. (1992), Bessembinder and Chan (1998), and Sullivan et al. (1999). Allen and Karjalainen (1999) and Ready (2002) use the buy-and-hold return as benchmark, but find that the MA profitability is not convincing. Han et al. (2013) and Shynkevich (2012) find that the MA trading rule can beat the buy-and-hold benchmark, but they test the strategy on risk or industry portfolios rather than on broad-based indices. To

Table 7
ETF and index performance comparison using the standard MA strategy.

Long MA	(1) SPY	(2) S&P500	(3) Diff	(4) DIA	(5) DJIA	(6) Diff	(7) QQQ	(8) NASDAQ-100	(9) Diff
(Days)	From 02/01/1993			From 01/20/1998			From 03/11/1999		
5	1.54	2.27	−0.73	1.64	1.26	0.37	−3.84	−6.82	2.98
10	1.18	2.23	−1.05	2.54	0.75	1.78*	−1.10	−2.54	1.44
20	2.83	3.10	−0.26	3.48	4.00	−0.52	4.71	4.01	0.69
30	4.48	4.76	−0.29	2.99	2.83	0.16	4.99	5.49	−0.50
40	3.04	3.24	−0.20	1.87	2.27	−0.40	6.62	5.26	1.36
50	4.16	4.79	−0.63	3.24	2.82	0.42	8.23	5.97	2.26
60	5.16	5.38	−0.22	2.39	2.81	−0.41	7.77	7.60	0.18
70	5.50	6.21	−0.71	3.27	2.96	0.31	6.48	6.04	0.44
80	6.68	6.52	0.16	2.71	2.91	−0.21	8.07	6.61	1.46
90	5.64	5.74	−0.10	3.55	3.79	−0.24	8.35	8.44	−0.08
100	6.04	5.87	0.18	4.20	3.93	0.27	6.26	6.21	0.06
110	5.59	6.00	−0.41	3.70	3.68	0.03	5.76	5.99	−0.23
120	5.40	6.12	−0.72	3.36	3.00	0.36	6.45	5.92	0.53
130	5.73	5.40	0.33	2.89	2.75	0.14	6.49	6.04	0.45
140	6.16	6.41	−0.25	4.12	3.87	0.25	4.80	5.99	−1.20
150	7.00	7.43	−0.43	3.48	3.63	−0.14	5.39	4.66	0.73
160	7.06	7.53	−0.47	4.12	4.44	−0.32	5.48	3.55	1.93
170	7.59	7.73	−0.14	3.65	4.23	−0.57	6.03	3.94	2.09
180	7.49	7.43	0.06	3.32	4.10	−0.78	5.52	4.63	0.89
190	7.52	7.69	−0.18	3.19	3.34	−0.16	5.08	4.67	0.41
200	8.30	8.26	0.04	2.68	2.59	0.09	4.58	4.64	−0.05
Rt Corr	97.75%			98.13%			92.41%		
OC Rt Corr	84.59%			80.20%			83.58%		
Buy and Hold	10.35	10.30	0.04	8.82	8.75	0.07	9.40	9.41	−0.01
Market	10.35	10.35		8.39	8.39		7.50	7.50	

In this table we test the standard MA strategy on three major market indices S&P500, Dow Jones Industrial Average (DJIA), and Nasdaq-100, in comparison with their tracking ETFs: SPY, DIA, and QQQ (formerly QQQQ). The short-term moving average is 1 day (the ETF price) and the long-term MA lag lengths ranges from 5 to 200 days as listed in the first column. There is no band or transaction cost. All results are annualized MA strategy returns. The difference (*Diff*) of each pair is calculated by subtracting the index performance from the ETF performance. Statistical significance is calculated using a standard t-test on daily returns. At the bottom of this table, we also report return correlations (*Rt Corr*) and the open-to-close return correlation (*OC Rt Corr*) of each ETF-index pair, the annualized buy-and-hold return of each security (*Buy-and-Hold*), as well as the value-weighted market return over the same period (*Market*). Results reported in columns 2 through 10 are in percentage. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

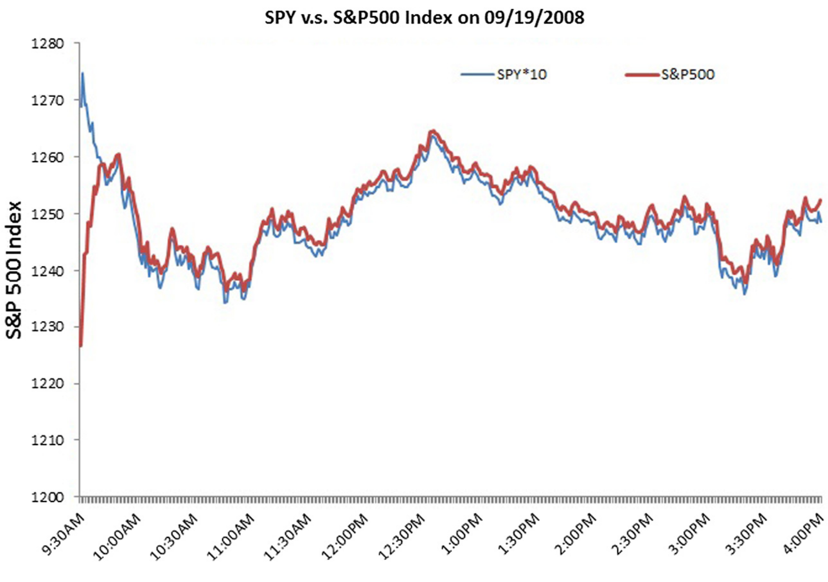

Fig. 3. Intraday price chart for SPY multiplied by 10 (SPY * 10) and the S&P500 index on September 19, 2008.

summarize, Table 7 finds that while the standard MA strategies do generate positive returns on indices as reported in the literature, they underperform the passive buy-and-hold benchmark strategy. We also repeat the ETF/Index comparison using the Sharpe ratio, the CAPM alpha, and the appraisal ratio performance measures, and the results are similar.

Table 8
Liquidity and MA strategy return.

Panel A: No transaction cost

Long MA	High Liq (Top 25%)			Quartile 2			Quartile 3			Low Liq (Bottom 25%)		
(Days)	QUIMA	Standard MA	Diff	QUIMA	Standard MA	Diff	QUIMA	Standard MA	Diff	QUIMA	Standard MA	Diff
5	11.63	0.02	11.61***	13.46	1.00	12.46***	15.29	1.35	13.94***	14.46	1.77	12.69***
10	5.77	0.47	5.30***	7.18	1.32	5.85***	8.44	2.08	6.36***	7.40	1.43	5.97***
20	7.49	3.29	4.20***	7.44	3.33	4.11***	8.79	3.93	4.85***	7.55	3.26	4.30***
30	7.08	3.95	3.12***	7.03	4.34	2.69***	8.20	4.91	3.29***	7.29	4.01	3.28***
40	6.61	3.92	2.70***	6.60	4.05	2.55***	7.56	4.75	2.80***	6.50	4.20	2.30***
50	6.54	4.70	1.84***	6.85	5.27	1.59***	7.33	5.20	2.14***	6.54	5.09	1.45***
60	6.22	4.83	1.39***	6.45	5.46	0.99***	7.19	5.55	1.64***	6.16	5.18	0.98**
70	6.10	4.97	1.13***	6.37	5.22	1.15***	6.82	5.65	1.17***	5.93	5.26	0.67*
80	6.13	5.47	0.65*	6.47	5.81	0.67**	6.95	6.22	0.73**	6.25	6.03	0.21
90	6.38	5.85	0.53*	6.84	6.15	0.68*	7.16	6.48	0.68**	6.39	6.25	0.13
100	6.19	5.94	0.26	6.60	6.34	0.27	7.17	6.49	0.68**	6.52	6.19	0.33
110	6.01	5.90	0.11	6.48	6.22	0.26	7.03	6.28	0.74**	6.35	6.04	0.31
120	6.09	5.85	0.25	6.44	6.40	0.04	6.95	6.29	0.67*	6.19	5.98	0.21
130	6.21	5.80	0.41	6.68	6.45	0.23	6.63	6.27	0.36	6.04	5.94	0.09
140	6.15	5.79	0.36	6.54	6.59	−0.05	6.86	6.35	0.51*	5.97	6.21	−0.23
150	6.35	6.05	0.30	6.46	6.57	−0.11	6.63	6.39	0.24	5.65	6.13	−0.48
160	6.27	6.23	0.04	6.30	6.66	−0.36	6.51	6.37	0.15	5.63	6.00	−0.38
170	6.14	6.36	−0.22	6.06	6.64	−0.58**	6.24	6.24	0.00	5.49	6.00	−0.50*
180	6.20	6.55	−0.35**	6.10	6.56	−0.45*	6.27	6.30	−0.03	5.49	5.90	−0.41
190	6.37	6.70	−0.33*	6.15	6.40	−0.24	6.20	6.48	−0.28	5.39	5.85	−0.47
200	6.31	6.78	−0.47**	6.11	6.48	−0.36*	6.32	6.52	−0.20	5.65	6.04	−0.39

Panel B: With transaction cost

Long MA	High Liq (Top 25%)			Quartile 2			Quartile 3			Low Liq (Bottom 25%)		
(Days)	QUIMA	Standard MA	Diff	QUIMA	Standard MA	Diff	QUIMA	Standard MA	Diff	QUIMA	Standard MA	Diff
5	7.55	−2.08	9.63***	8.85	−1.47	10.32***	9.45	−2.89	12.34***	4.61	−3.86	8.46***
10	2.58	−0.98	3.55***	3.67	−0.23	3.90***	3.05	−1.38	4.43***	0.63	−2.47	3.10***
20	5.26	2.30	2.96***	5.21	2.24	2.96***	4.52	1.69	2.83***	2.42	0.72	1.70**
30	5.24	3.26	1.98***	5.03	3.36	1.67***	4.50	3.08	1.42*	2.48	1.77	0.71
40	5.17	3.19	1.98***	4.64	3.30	1.33***	3.98	2.55	1.42**	2.46	2.09	0.36
50	5.07	4.09	0.98**	5.36	4.25	1.11**	4.06	3.30	0.76*	2.77	3.12	−0.36
60	4.97	4.34	0.63	4.94	4.64	0.30	4.04	4.06	−0.02	2.39	3.32	−0.93
70	4.86	4.47	0.39	4.90	4.41	0.49	3.78	4.25	−0.47	2.46	3.20	−0.75*
80	4.82	4.84	−0.02	5.26	5.18	0.07	4.15	4.70	−0.55	2.75	3.97	−1.22***
90	5.18	5.28	−0.09	5.76	5.59	0.16	4.70	5.11	−0.42	2.90	4.05	−1.15***
100	4.98	5.41	−0.43	5.67	5.74	−0.07	4.58	5.04	−0.46	2.97	3.67	−0.69*
110	4.85	5.35	−0.50*	5.58	5.65	−0.07	4.55	5.04	−0.49	2.74	3.40	−0.67*
120	4.99	5.44	−0.44	5.53	5.69	−0.16	4.33	5.25	−0.92	2.78	3.38	−0.60
130	5.21	5.50	−0.29	5.57	5.66	−0.09	3.99	5.04	−1.05*	2.36	3.27	−0.90*
140	5.21	5.47	−0.26	5.68	6.01	−0.33	4.00	4.94	−0.93*	2.42	3.16	−0.74
150	5.45	5.65	−0.20	5.65	6.08	−0.43	4.13	4.93	−0.80	1.86	3.17	−1.30**
160	5.38	5.79	−0.41*	5.54	6.09	−0.55*	4.11	4.96	−0.85*	1.99	3.03	−1.04*
170	5.29	6.01	−0.72***	5.32	6.01	−0.70**	3.81	4.88	−1.07**	2.04	3.16	−1.12***
180	5.37	6.14	−0.77***	5.38	6.03	−0.65**	3.90	4.91	−1.01**	2.05	3.08	−1.03***
190	5.58	6.23	−0.64***	5.59	6.07	−0.49*	3.91	5.10	−1.19***	2.16	3.57	−1.40***
200	5.53	6.35	−0.82***	5.64	6.20	−0.56**	3.96	5.24	−1.28***	2.28	3.66	−1.37***
Benchmark performance		Return (%)			Return (%)			Return (%)			Return (%)	
Buy and Hold:		9.80			9.84			9.44			9.67	
Market Return:		8.54			8.61			8.70			8.71	

This table reports annualized MA strategy returns on ETFs by liquidity quartiles based on the Amihud (2002) illiquidity measure. In Panel A there is no transaction cost while in Panel B we apply the time-varying transaction cost as detailed in Section 4.3. Within each quartile, we compare the QUIMA strategy with the standard MA strategy across different long-term MA lag lengths. The short-term moving average is 1 day (the ETF price) and there is no band. Difference (*Diff*) is the performance of the QUIMA strategy minus that of the standard MA strategy. For all annual returns, we first calculate the time-series average for each ETF, then average across all ETFs within that liquidity group. Significance is based on bootstrapping 10,000 times. The last two rows in Panel B also list the average annual return of the buy-and-hold strategy on sample ETFs and the average value-weighted market return. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively. Results reported in columns 2 through 13 are in percentage.

5.4. Discussion

5.4.1. Liquidity and MA performance

Our findings in Sections 5.2 and 5.3 contrast Han et al. (2013) and Shynkevich (2012) who find that the MA strategy tested on stock portfolios outperforms the buy-and-hold benchmark by a large margin. On the other hand, Allen and Karjalainen (1999) and Ready (2002) do not find any profitability when testing the MA strategy on the S&P500 and the DJIA indices. Therefore, liquidity

Table 9
Opening gaps for ETFs and indices.

Panel A: Loss from opening gap on signal days							
	Number of signal days				Loss from opening gap		
Security	Confirmed	Reverted	Rvt / Cfm	Total	Days by Gap	Pct(%)	Avg Loss (bps)
SP500:	1050	666	0.6343	1716	180	10.49	1.0455
SPY:	1048	770	0.7347	1818	548	30.14	9.9296
DJIA:	777	525	0.6757	1302	165	12.67	2.8479
DIA:	793	577	0.7276	1370	430	31.39	10.0482
NASDAQ-100:	789	547	0.6933	1336	407	30.46	17.7006
QQQ:	777	591	0.7606	1368	384	28.07	13.0263

Panel B: Example: Opening gap on September 19, 2008							
Security	Previous close	10-Day MA	OPEN	HIGH	LOW	Close	MA Ret
SP500	1206.51	1224.94	1213.11	1265.12	1213.11	1255.08	2.57%
SPY	120.07	122.88	126.70	128.00	116.52	124.12	−2.04%

This table focuses on the performance loss caused by opening gaps for the QUIMA strategy on signal days when trading on indices and their corresponding ETFs. The short-term moving average is 1 day (the ETF price) and the long-term MA length is 10 days. There is no band or transaction cost. In Panel A, we report the total number of MA signal days with *Confirmed* and *Reverted* MA signals for each index/ETF. *Rvt / Cfm* is the ratio of the number of reverted MA signal days to the number of confirmed MA signal days. We also report the signal days caused by opening gap (*Days by Gap*) as a percent of the total number of MA signal days (*Total*). The last column, average gap loss (*Avg Loss*), is calculated by dividing the total loss from opening gaps by the total number of signal days (*Total*). Panel B uses September 19, 2008 as an example to show how opening gaps affect the performance of the QUIMA strategy differently on S&P500 index versus on SPY. Notice that the SPY prices have been adjusted for dividends.

may play an important role in the profitability of the MA technical trading strategy. In this section we investigate cross-sectionally the relationship between ETF liquidity and the performance of the MA strategy. Our prior expectation is that even though ETFs in general have superior liquidity, we should still see MA perform stronger in relatively illiquid ETFs. On the other hand, since our transaction cost is also liquidity based, applying a transaction cost to the MA strategy will mitigate the performance difference between liquid and illiquid ETFs.

As for liquidity measures, we choose to use the Amihud (2002) illiquid measure which is essentially a volume denominated volatility measure that increases either as volatility increases or when trading volume decreases. We repeat in Table 8 the main back-testing of MA strategies on liquidity quartiles as measured by the Amihud illiquid measure, in both cases with and without transaction cost. We also test two other liquidity measures: trading volume and bid–ask spread, and get similar results.

Table 8, Panel A, shows similar results as found in Table 5 across all four liquidity groups. However, when there is no transaction cost, both strategies perform better on relatively illiquid ETFs. Although not reported here, a simple univariate regression shows that cross-sectionally, MA performance increases with all three illiquidity measures significantly at the 1% level. Still, in none of the liquidity groups can the MA strategy return beat the buy-and-hold return. Panel B repeats the previous results after imposing our time-varying liquidity-based transaction cost detailed in Section 4.3. As we can see, the performance of the low liquidity quartile dropped a lot due to higher transaction costs. The other three quartiles are pretty close in MA strategy return. In addition, the QUIMA strategy is hit harder by the transaction costs because it trades more often than the standard MA strategy. Overall, our findings indicate that the market is pretty efficient in pricing ETF liquidity into the profitability of MA strategies. Less liquid ETFs may look better when back-tested without transaction cost, but in actual trading transaction cost will kill the deal.

5.4.2. *Why does the QUIMA strategy perform worse on ETFs?*

Looking back at Table 6 on both ETFs and indices, we see that despite the performance difference between ETFs and indices, ETFs do track their corresponding indices closely as their daily return correlations are all higher than 90%. However, the open-to-close correlations are much lower in the 80% range. Why does the exact same strategy dramatically underperform when applied on ETFs?

One possibility, as pointed out by Bessembinder and Chan (1998), is the omission of dividends in index data. ETF data, on the other hand, do contain daily return information that is adjusted for dividends.[6] This should not be a problem in this study since we adjust all index prices to reflect dividend payment by using dividend information extracted from the ETF data. We also test the unadjusted case and the result is the same.

Instead, we find that the price discontinuity at the opening, i.e. opening gaps, plays a major role in lowering ETF performance. ETFs have much larger opening gaps than indices, often skipping the long-term moving average price. Therefore, when trading ETFs buyers have to buy at a higher price after a gap up, and sellers take a lower price after a gap down. In other words, our findings show that ETFs are more efficient than indices in reflecting information at opening, preventing investors from trading the MA crossover signal at a desired price.

Let us focus on the open prices of ETFs and indices because we see a much reduced open-to-close return correlation in Tables 6 and 7. Moreover, in Table 6, while we document lower MA return on SPY and DIA, there is not much difference in MA returns for the

[6] Elton et al. (2002) find there is about a 10 bps annual performance drag from SPY (the ETF tracking the S&P500 index) because they put dividend in a non-interest-bearing account, but this is too small to explain the large performance difference we find in this study.

QQQ and the NASDAQ-100 index. In fact, we notice that the literature on MA trading strategy is mainly focused on the S&P500 and DJIA indices. Therefore, it is reasonable to hypothesize that it is trader exploitation that drives down the performance on ETFs for the two heavily back-tested indices. Specifically, when many investors are following the same MA strategy, they buy (sell) roughly at the same time when they see a golden (death) cross MA signal. During normal trading hours, this type of simultaneous trading can be well absorbed by the superb liquidity of index ETFs. However, as liquidity drops sharply during after-hours trading, we should expect a larger opening gap on ETFs when investors rush to trade at the opening price if an MA crossover occurs because of the overnight market movement.

Table 9 provides a detailed summary of opening gaps on MA signal days for both ETFs and indices. The first few columns in Panel A focus on the ratio of reverted to confirmed intraday crossovers (*Rvt/Cfm*), which is larger for ETFs than for indices. This means that for all three indices the QUIMA strategy encounters more reverted intraday crossovers on ETFs than on indices. The last three columns summarize the performance drag from opening gaps, including the number of days an MA crossover occurs at the opening gap, its percentage among all MA signal days, and the average loss from opening gaps in each signal day. As we can see, the S&P500 and DJIA indices have a much lower probability of being affected by opening gaps than their corresponding ETFs. The average daily performance losses on MA signal days due to opening gap are only 1 and 3 bps for the S&P500 and the DJIA indices, respectively, while on ETFs the losses are about 10 bps. However, we find the opposite for the NASDAQ-100 index, which has larger, more frequent opening gaps than those of QQQ.

Panel B is an example of opening gap on the Friday of September 19, 2008, when the market was gyrating after the fall of Lehman Brothers. We can see on 09/19/2008 the S&P500 index did not gap up too much, but the corresponding ETF (SPY) gapped up more than 6%, well above the 10-day MA at which an investor would want to buy. The QUIMA strategy using market order to buy immediately at opening could have reaped 2.57% in profit on S&P500 index, but instead suffered a loss of 2.04% that day on the SPY.[7] Fig. 3 is the intraday price chart for SPY and the S&P500 index on that day. The two time series move very closely throughout the day, except that they open at dramatically different levels before converging after about 10 min.[8] This evidence supports the conclusion that investor exploitation as reflected by large opening gaps reduces MA performance on ETFs.

5.4.3. The 10-day moving average

One interesting feature in Table 5 is that the 10-day long-term MA performs worse than the nearby MA lengths. Since the 10-day moving average is an important trend indicator for stocks in short-term, it is possible that trader exploitation drives away profit for the 10-day MA strategy. Fig. 4 takes a close look at the performances of two MA strategies across different long-term MA lag lengths. Subplots (a) and (b) illustrate the performances of long-term MA lag lengths ranging from 5 to 250 days, and from 5 to 50 days zoomed in, respectively. As we can see, there is a clear performance dent around the 10-day MA length when the investor uses the QUIMA strategy, but not for the standard MA strategy. To quantitatively measure the significance of the performance dent caused by the 10-day MA, we first fit all these annual returns into a quadratic regression, then estimate the significance of the return of 10-day MA based on the standard deviation of the error term. The *p*-value of the 10-day MA, denoted by P_{10} on the graph is less than 5%.

Naturally, we would like to find out if this is really due to trader exploitation or simply a statistical fluke. One possible way is to test on some other liquid stocks and market indices. If it is due to trader exploitation, we should see this pattern stronger on tradable stocks than on non-tradable indices. Subplot (c) of Fig. 4 compares the 5- to 50-day MA lag lengths on the 30 DJIA component stocks during the time period from February 1993 to December 2016. We notice that MA strategy performance decreases around the 10-day MA lag length as well. The performance dent caused by the 10-day MA is also significant.

Finally, since academic publications affect the trading behavior of investors (see, e.g., Huang (2008), Huang and Huang (2013) and Schwert (2003)), we would like to see if the 10-day MA behaves differently before the publication of Brock et al. (1992) which pioneers a plethora of academic studies on the MA technical trading rule. Since there is no earlier history for ETFs before 1993, we use the DJIA component stocks for the test. Subplot (d) of Fig. 4 looks at those DJIA component stocks as of December 31, 1992, during the 10-year time period from January 1983 to December 1992. As we can see in the ten years prior to the end of 1992, the 10-day MA lag length does not under-perform surrounding MA lag lengths. Such evidence implies that as the popularity of the MA crossover trading strategy grew with recent academic publications, the 10-day MA length received more trader exploitation than other MA lag lengths.

Fig. 5 further looks at this performance dent around the 10-day MA across different ETF types. Based on the reported significance, we see our finding persists in all the three major categories of ETFs: index, style, and sector. In unreported tables, we also run a “resonance test” for all different MA lag lengths to see if there is an exceptionally high probability for MA crossovers of other MA lag lengths to occur on days with a 10-day MA crossover. We do not find anything special about the 10-day MA length. In other words, the 10-day MA itself is not technically important. It is investor trading activity that drives down the performance of the 10-day MA strategy.

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[7] Note that in this example a limit order at the 10-day MA level would avoid the loss from opening gap for SPY. However, on average limit order fares slightly worse than market order for short long-term MA lags as shown in Table 2.

[8] A July 10, 2017 WSJ article also claims that ETFs do not closely track the holding stocks at opening and close. https://www.wsj.com/articles/a-smarter-approach-to-etf-investing-1499652661.

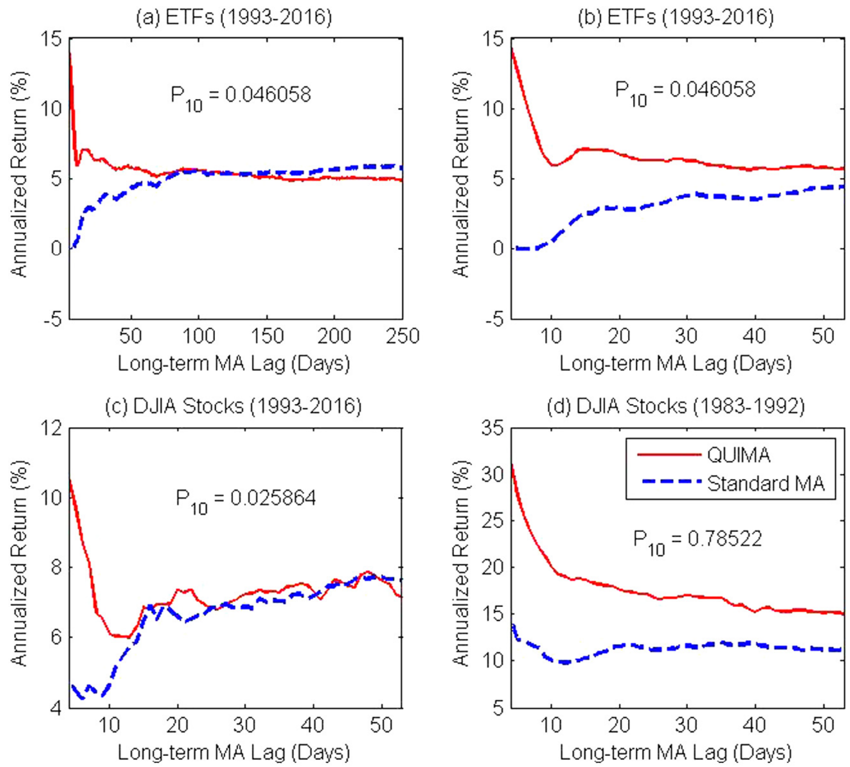

Fig. 4. Figures (a) through (d) compare the MA performance across different long-term MA lag lengths for both the QUIMA and the standard MA strategies. The short-term MA is set at 1 day (the ETF/stock price), and there is no band or transaction cost. Figures (a) and (b) illustrate the performances of MA lag lengths ranging from 5 to 250 days, and from 5 to 50 days, respectively. These two figures use our main data set of 198 ETFs from February 1, 1993 to December 31, 2016. Figure (c) compares the 5 to 50-day MA lengths on the 30 DJIA component stocks during the same time period from February 1993 to December 2016. Figure (d) instead looks at those DJIA component stocks as of December 31, 1992, during the time period from January 1983 to December 1992. All returns are annual returns averaged within each ETF, then across 198 ETFs. We calculate the statistical significance of the underperformance of 10-day MA length (P_{10}) using quadratic regression. p-Values for the QUIMA strategy are printed along each figure.

6. Conclusion

While many studies find moving-average (MA) trading strategies profitable, a question remains whether retail investors can utilize such profitability in practice. In this study we focus on the implementation of MA strategies using ETFs and its implications for retail investors. Among the potential factors that influence the performance of such strategies, we consider transaction costs, performance benchmarks used, instruments used for back-testing, and the timing of investors' responses to technical trading signals. Specifically, we backtest the performance of MA strategies on US equity ETFs against the buy-and-hold benchmark. We also compare the MA performance of these ETFs and their underlying non-tradable indices. Lastly, we propose and test a quasi-intraday moving-average (QUIMA) strategy that allows the investor to trade immediately when an MA crossover occurs.

We find that while MA strategies generate positive average returns, they are lower than those of the buy-and-hold strategy using the same asset in our sample. In another word, implementing the MA technical trading rule with an ETF did not earn significant excess returns relative to just holding the ETF over our sample period. In addition, our results show that MA strategies have lower Sharpe ratios than the buy-and-hold strategy. On the other hand, MA strategies have better factor-adjusted performance, such as the CAPM alpha, than the BH strategy. Interestingly, we also find that the profitability of MA strategies on an ETF is lower than that of these strategies on the same ETF's (non-tradable) underlying equity index. We provide evidence that one potential reason for this decline in the profitability is that ETFs on average have larger opening gaps than do their underlying equity indices on days with MA crossover signals. Largely motivated by this observation, the proposed QUIMA strategy indeed performs slightly better than the standard MA strategy that only trades at daily close.

To summarize, our findings indicate that the simple buy-and-hold strategy using long-only U.S. equity ETFs outperforms standard MA strategies in terms of either the mean return or the Sharpe ratio. MA strategies provide better factor-adjusted performance, however. We should note that both the standard MA and QUIMA strategies examined in this study are implemented using daily data. A potential line of inquiry worth pursuing is to test MA strategies using high frequency and after-hours trading data and to examine, among other things, the impact of sudden fluctuations in intraday prices or prices during after-hours trading.

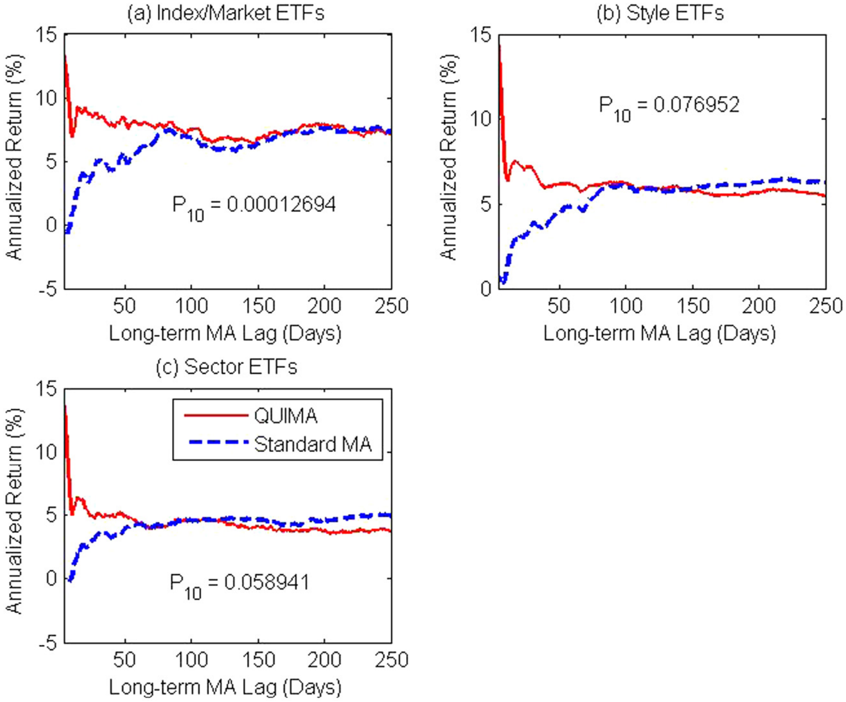

Fig. 5. Figures (a) through (c) compare the performance dent around the 10-day MA lag length across different ETF types. The short-term MA is set at 1 day (the ETF/stock price), and there is no band or transaction cost. Each figure presents the average result for one of the three ETF types: Index/market (15 ETFs), Style (100 ETFs), and Sector (83 ETFs). All returns are annual returns averaged within each ETF, then across ETFs of that type. We calculate the statistical significance of the underperformance of 10-day MA length (P_{10}) using quadratic regression. p-Values for the QUIMA strategy are printed along each figure.

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